

**Developing Vehicle-Based Advanced Warning  
System for Driver Drowsiness Based on a Hybrid  
Algorithm**

A thesis  
submitted in fulfilment  
of the requirement for the degree  
of  
Doctor of Philosophy  
at the  
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by

**MURAD A. KARRAR**

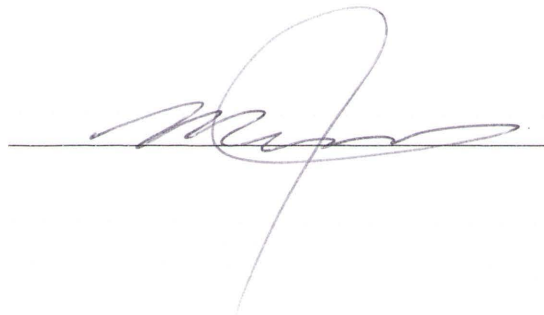
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2010

## **Certificate of authorship**

I certify that the work in this thesis has not previously been submitted for a degree, nor has it been submitted as part of requirements for a degree.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Candidate

A handwritten signature in blue ink, consisting of a large, stylized 'M' followed by a horizontal line and a long, sweeping underline that extends to the right.

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## Preface

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# Glossary

## Acronyms

## Detailed

802.11	a set of standards for wireless networks
ABM	Advanced Brain Monitoring
ACARP	Australian Coal Association Research Programme
AFM	Advanced Fatigue Management
AMP	Alertness and Memory Profiler
ANOVA	analysis of variance
APSR	averaged power spectrum ratio
ARL	Atlas Researchers Ltd
ARRB	Australian Road Research Board
ASL	Applied Science Laboratories
AUC	area under the curve
B&W	Black & White
BFM	Basic Fatigue Management
BMI	body mass index
BP	Blood Pressure
C4	Central EEG measurements
CAM	Video camera
CRF	Fiat Research Centre
DARPA	Defense Advanced Research Projects Agency
DC	direct current
DFFT	discrete fast Fourier transform
DSP	Digital Signal Processing
ECG	electrocardiogram
ECU	Engine Control Unit
EDA	electrodermal activity
EDR	electrodermal response
EDVTCS	Engine Driver Vigilance Telemetric Control System
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ESS	Epworth Sleepiness Scale
ETS	Eye tracking system
FFT	Fast Fourier Transform

<b>Acronyms</b>	<b>Detailed</b>
Fp1, Fp2	Frontal Polar EEG measurements
g	Grams
GB	Gigabyte
GEE	generalised estimating equations
GHz	Giga Hertz
HFLC	high-fat/low carbohydrates
HREC	Human Research Ethics Committee
Hz	Hertz
IrDA	Infrared Data Association
kg	Kilogram
LAN	local area network
LCB	Locus-of-control
LED	light emitting diodes
LFHC	low-fat/high carbohydrates
LOC	left outer canthus
MB	Megabyte
MBDAR	The maximum of the MBIARs of the 10 values
MBIAR	Maximum Body movement Increase Amplitude Ratio
MFMC	medium-fat/medium carbohydrates
mg	milligram
MINDS	MicroNod Detection system
ml	millilitre
MMBDAR	Maximum Body movement Decrease Amplitude Ratio
MMBIAR	The maximum of the MBIARs of the 10 values
MPEG4	Moving Picture Experts Group-4
MPSR	maximum power spectrum ratio
msec	milliseconds
MSLT	Multiple Sleep Latency Test
MUARC	Monash University Accident Research Centre
NCSDR	National Center on Sleep Disorders Research (USA)
NHTSA	National Highway Traffic Safety Administration (USA)
NREM	non rapid eye movement
NSW	New South Wales
NTC	National Transport Commission (Australia)
O2	Occipital EEG measurements

**Acronyms**

PAL

PC

PERCLOS

POMS

PS

PSG

RAM

REM

RF

RLL

ROC

ROC

RPSR

RTA

SAS

SD

SE

sec

SEM

Sen

Spec

SSS

TAC

TBIAR

UK

US

USA

USB

USD

UTS

VAS

VRTC

Wi-Fi

**Detailed**

Phase Alternating Line

Personal Computer

percentage of eyelid closure

Profile of Mood States

Power Spectral

Polysomnography

Random-access memory

Rapid Eye Movement

radio frequency

Residual log-likelihood

right outer canthus

Relative Operating Characteristic

relative frequency band power spectrum ratios

Road and Traffic Authority, NSW (Australia)

statistical analysis software

Standard Deviation

Standard Error

Seconds

Slow Eye Movement

Sensitivity

Specificity

Stanford Sleepiness Scale

Transport Accident Commission, Victoria (Australia)

Test Body movement Increase Amplitude Ratio

United Kingdom

United States

United States of America

Universal Serial Bus

United States Dollar

University of Technology, Sydney

Visual Analogue Scale

Vehicle Research & Test Center (USA)

Wireless LAN (Local Area Network)

## Abstract

Fatigue is a major public health issue causing substantial emotional and financial burden on society. Driver fatigue is identified in nearly 20-30% of road fatalities, and can cost around AUD 3 billion per year. Providing drivers with early warning systems for fatigue could minimise fatigue-related road accidents. A car driving simulator study was conducted and physiological data such as electroencephalography (EEG), eye activity, movement sensor data, video and questionnaire information were obtained for the purposes of developing a drowsiness detection algorithm. The study was conducted at the Monash University Accident Research Centre (MUARC) where sixty non-professional drivers aged between 20-60 years were recruited. The study was conducted in the afternoon and the driving sessions lasted up to 3 hours of monotonous day and night driving scenarios with realistic scenery.

The preliminary analysis identified sections of data where clear episodes of drowsiness were evident. The analysis revealed that it was possible to detect drowsiness from a combination of physiological signals consisting of EEG, car seat movements and eye activity. Once the association between episodes of drowsiness and various signals were established, statistical analysis was performed on the entire data set. Two types of EEG processing were employed at this stage based on EEG alpha power and alpha burst analysis. A significant association was established between the probability of drowsiness and EEG alpha activity, with alpha burst duration resulting in a better association. Drowsiness detection algorithms based on these two methods were then developed.

The association established between drowsiness and the seat movement signals was far less than that between drowsiness and the alpha signals. The seat movement signals were then combined with both methods of alpha analysis. Adding seat movement signal to either of the two EEG methods resulted in improved associations with drowsiness with alpha burst association still being superior. The algorithm based on the combinations of alpha burst and seat movements formed the basis for the new hybrid algorithm.

Subjective measures of drowsiness, lifestyle and behaviour were also examined in this research and validated against video ratings of fatigue. It was shown that increased anxiety, anger and an unhealthy diet were associated with an increased probability of drowsiness.

The findings of this research can serve as a foundation for designing future vehicle-based fatigue countermeasure devices as well as highlight potential difficulties and limitations. Such driver fatigue studies will also benefit from further investigations of driver lifestyle and behavioural factors.